Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval

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**A R T I C L E   I N F O**

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**A B S T R A C T**

This paper presents a novel feature extraction algorithm called local ternary co-occurrence patterns (LTCoP) for biomedical image retrieval. The LTCoP encodes the co-occurrence of similar ternary edges which are calculated based on the gray values of center pixel and its surrounding neighbors. Whereas the standard local derivative pattern (LDP) encodes the co-occurrence between the first-order derivatives in a specific direction. The existing LDP is a specific direction rotational variant feature where as our method is rotational invariant. In addition, the effectiveness of our algorithm is confirmed by combining it with the Gabor transform. To prove the effectiveness of our algorithm, three experiments have been carried out on three different biomedical image databases. Out of which two are meant for computer tomography (CT) and one for magnetic resonance (MR) image retrieval. It is further mentioned that the database considered for three experiments are OASIS–MRI database, NEMA–CT database and VIA/J–ELCAP database which includes region of interest CT images. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to LBP, LTP, local tetra patterns (LTrP) and LDP with and without Gabor transform.

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1. Introduction

Biomedical image retrieval is an active research topic in medical imaging. The medical data is in different format such as computer tomography (CT), magnetic resonance images (MRI), ultrasound (US), X-ray etc. Handling of this data by human annotation is a cumbersome task thereby, arousing a dire need for some familiar search technique i.e. content based image retrieval (CBIR).

The feature extraction plays an important role in CBIR whose effectiveness depends upon the method adopted for extracting features from given images. The visual content descriptors are either global or local. A global descriptor represents the visual features of the whole image; whereas a local descriptor represents the visual features of regions or objects to describe the image. These are arranged as multidimensional feature vectors and construct the feature database. For similarity distance measurement many methods have been developed like Euclidean distance ($L_2$), $L_1$ distance etc. Selection of feature descriptors and similarity distance measures affect retrieval performances of an image retrieval system significantly. The previously available literature on biomedical image retrieval is presented in Refs. [1–5].

The brief description about the features which are previously available for biomedical imaging is given as follows. Hersh et al. [6] have done ImageCLEF medical image retrieval task (ImageCLEFmed) to improve understanding and system capability in search for medical images. They described the development and use of a medical image test collection design to facilitate research with image retrieval systems and their users. The bit plane histogram and hierarchical bit plane histogram along with cumulative distribution function (CDF) is presented in Ref. [7] for CT and MRI image retrieval. Classification of benign and malignant breast masses based on shape and texture features in sonography images is proposed in Ref. [8]. The blood cell image retrieval using color histogram and wavelet transform can be seen in Ref. [9]. Quellec et al. [10] proposed the optimized wavelet transform for medical image retrieval by adapting the wavelet basis, within the lifting scheme framework for wavelet decomposition. The weights are assigned between wavelet sub-bands. They used the diabetic retinopathy and mammographic databases for medical image retrieval. The wavelet transform based brain image retrieval is presented in Ref. [11]. The co-occurrence matrix based retrieval of medical CT and MRI images in different tissues is can be seen in Ref. [12]. Further, the image retrieval of different body parts is proposed in Ref. [13] which employs color quantization and wavelet transform. In Ref. [14] a boosting framework for visuality-preserving distance metric learning is proposed for medical image retrieval. The mammographic images and dataset from Image CLEF...
are used for performance evaluation. Nakayama et al. [15] investigated four objective similarity measures as an image retrieval tool for selecting lesions similar to unknown lesions on mammograms.

The features [6–15] have motivated us to propose a novel feature which integrates the concept of co-occurrence matrix and local ternary patterns for biomedical image retrieval. The previously available pattern based features are discussed as follows. Ojala et al. [16] proposed the local binary patterns (LBP) which can show better performance as well as less computational complexity for texture classification. Success of LBP variants in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification [16–21], face recognition [22–24], object tracking [25], image retrieval [26–30], palmprint matching [31] and pedestrian detection [32].

Rotational invariant LBP variance for texture classification using feature distributions is proposed in Ref. [19]. Guo et al. developed the completed LBP (CLBP) scheme for texture classification [20]. Further, they [21] have developed the learning framework which can estimate the optimal pattern subset of interest by simultaneously considering the robustness, discriminative power and representation capability of texture features. They integrated these features with existing LBP variants such as conventional LBP, rotation invariant patterns, local patterns with anisotropic structure, completed local binary pattern (CLBP) and local ternary pattern (LTP) to derive new image features for texture classification. However, LBP provides all directional first-order derivatives.

To address this problem, LDP [22] is proposed for face recognition, where the authors considered LBP as non-directional first-order local patterns collected from the first-order derivatives and extended the same approach for nth-order local derivative patterns. The versions of LBP and LDP in the open literature cannot adequately deal with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc. In order to address this problem, local ternary pattern [23] has been introduced for face recognition under different lighting conditions. LBP, LDP and LTP extract the information based on the distribution of edges which are coded using only two directions (positive direction or negative direction). Subrahmanym et al. [26] have proposed the directional binary wavelet patterns (DBWP) for biomedical image retrieval. They integrated the binary wavelet transform (BWT) and LBP for feature extraction. Quantitative analysis of pulmonary emphysema using LBP is presented in Ref. [29]. They improved the quantitative measures of emphysema in CT images of the lungs by using joint LBP and intensity histograms.

The LBP, the LTP, the LDP and the co-occurrence matrix features have motivated us to propose the LTCoP for biomedical image retrieval. The main contributions of our method are as follows:

1. The proposed LTCoP encodes the co-occurrence of local ternary edges which are calculated based on the gray values of center pixel and its surrounding neighbors.
2. The LTCoP is robust to the different lighting conditions as compared to LBP and LDP.
3. The performance of the proposed method is confirmed by combining it with the Gabor transform.
4. The performance of the proposed method is analyzed with the difference distance measures.

The organization of the paper is as follows: In Section 1, a brief review of medical image retrieval and related work are given. A concise review of local patterns can further be visualized in Section 2. The multi-scale feature extraction, proposed system framework and analysis are presented in Section 3. Further, experimental results and discussions to support the algorithm can be seen in Section 4. Conclusions are derived in Section 5.

2. Local patterns

2.1. Local binary patterns (LBPs)

The LBP operator was introduced by Ojala et al. [16] for texture classification. Given a center pixel in the image, LBP value is computed by comparing its gray value with its neighbors as shown in Fig. 1 based on Eq. (1).

\[
LBP_{p,k} = \sum_{i=1}^{P} 2^{i-1} \times f_1(l(g_i) - l(gc))
\]  

\[
f_1(x) = \begin{cases} 
1 & x \geq 0 \\
0 & \text{else} 
\end{cases}
\]  

where \(l(g_i)\) is the gray value of the center pixel, \(l(g_i)\) is the gray value of its neighbors, \(P\) is the number of neighbors and \(R\) is the radius of the neighborhood.

![Fig. 1. Calculation of LBP and LTP operators.](image-url)
2.2. Local ternary patterns (LTPs)

Tan and Triggs [23] extended the LBP to three valued code called LTP, in which gray values in the zone of width \(\pm th\) around \(g_c\) are quantized to zero, those above \((g_c)+th\) are quantized to +1 and those below \((g_c)-th\) are quantized to -1, i.e., the indicator \(f_1(x)\) is replaced with 3-valued function (Eq. (3)) and binary LBP code is replaced by a ternary LTP code as shown in Fig. 1.

\[
f_1(x, l(g_c), th) = \begin{cases} 
1, & x>l(g_c)+th \\
0, & x-l(g_c) < th \\
2, & x<l(g_c)-th 
\end{cases} \quad (3)
\]

More details about LTP can be found in Ref. [23].

2.3. Local derivative patterns (LDPs)

Zhang et al. proposed the local derivative patterns (LDP) for face recognition [22]. They considered LBP as the non-directional first-order local pattern operator and extended it to higher-orders (nth-order) called LDP. LDP contains more detailed discriminative features as compared to LBP.

To calculate the nth-order LDP, the \((n-1)\)th-order derivatives are calculated according to \(0.45, 90\), and \(135\) directions, denoted as \(\text{LDP}^n_{i,j}(g_c)\). Finally nth-order LDP is calculated as

\[
\text{LDP}^n_{i,j}(g_c) = \sum_{p=1}^{P} 2^{p-1} \times f_2(l^{(n-1)}_{i,j}(g_c), l^{(n-1)}_{i,j}(g_{p})) \quad (4)
\]

\[
f_2(x,y) = \begin{cases} 
1 & \text{if } x \times y \leq 0 \\
0 & \text{else}
\end{cases} \quad (5)
\]

Fig. 2 illustrates the calculation of LDP in \(0^\circ\) direction and the detailed discussion is available in Ref. [22].

2.4. Local ternary co-occurrence patterns (LTCoPs)

The idea of LDP and LTP has motivated us to propose the LTCoP for biomedical image retrieval. Given a center pixel, the LTCoP is calculated based on the first-order derivatives in eight directions as shown in Fig. 2.

In proposed LTCoP, the first-order derivatives for a given center pixel \((g_c)\) are calculated as follows:

\[
l_f^i(g_c) = l_f^i(g_c) - l_f^i(g_{c-1}); \quad i = 1, 2, ..., P 
\]

\[
l_{f,R+1}^i(g_c) = l_{f,R+1}^i(g_c) - l_{f,R}^i(g_{c}); \quad i = 1, 2, ..., P 
\]

After calculation first-order derivatives, we code them based on the sign of derivative as follows:

\[
l_f^i(g_c) = f_1(l_f^i(g_c)) 
\]

\[
l_{f,R+1}^i(g_c) = f_1(l_{f,R+1}^i(g_c)) 
\]

The \(l_f^i(g_c)\) and \(l_{f,R+1}^i(g_c)\) are ternary values. Further, these ternary values are used for co-occurrence calculation for LTCoP as follows:

\[
\text{LTCoP} = \left[ f_3(l_f^1(g_c), l_{f,R+1}^1(g_c)), f_3(l_f^2(g_c), l_{f,R+1}^2(g_c)), ..., f_3(l_f^P(g_c), l_{f,R+1}^P(g_c)) \right] 
\]

\[
f_3(x,y) = \begin{cases} 
1 & \text{if } x = y = 1 \\
2 & \text{if } x = y = 0 \\
0 & \text{else}
\end{cases} \quad (11)
\]

LTCoP is the ternary pattern (0, 1, 2) which is further converted into two binary patterns by adopting the concept of LTP [23].

For the local pattern with \(P\) neighborhoods, \(2^n\) combinations of binary patterns are possible, resulting in feature vector length of \(2^n\). The computational cost of this feature vector is very high. In order to reduce the computational cost we consider the uniform patterns [19]. The uniform pattern refers to the uniform appearance pattern that has limited discontinuities in the circular binary representation. In this paper, those patterns which have less than or equal to two discontinuities in the circular binary representation are referred to as the uniform patterns and remaining patterns are referred to as non-uniform. Thus, the distinct uniform patterns for a given query image would be \(2|P-1\)+2 but deprived of rotational invariant. The possible uniform patterns for \(P=8\) can be seen in Ref. [19]. The rotational invariant LTCoP patterns (LTCoP1u2) can be constructed by considering all eight directional patterns to the same bin of histogram [19]. The distinct values for a given query image are \(P+2\) by using LTCoP1u2.

Fig. 2. Example for LDP and LTCoP calculation.
After identifying the local pattern, PTN (LBP or LTP or LDP or LTCoP) the whole image is represented by building a histogram using Eq. (12)

\[ H_2(l) = \frac{1}{N_1 \times N_2} \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_4(PTN(j,k), l); \quad l \in [0, L-1] \]  

(12)

\[ f_4(x, y) = \begin{cases} 
1 & \text{if } x = y \\
0 & \text{else} 
\end{cases} 
\]  

(13)

where, \( L \) represents the number of bins and \( N_1 \times N_2 \) represents the size of input image.

### 3. Multi-scale feature extraction and analysis

In literature [16,22,23], pattern based features are analyzed by combining with Gabor transform (GT). Thus in order to compare our results with the above methods we have presented the analysis of our method (LTCoP) with the Gabor transform.

#### 3.1. Gabor transform

Subrahmanyan et al. [27] have given the spatial implementation of the Gabor transform. A 2D Gabor function is a Gaussian modulated by a complex sinusoid. It can be specified by the frequency of the sinusoid \( \omega \) and the standard deviations \( \sigma_x \) and \( \sigma_y \) of the Gaussian envelope as follows:

\[ \psi(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{(-(x^2/\sigma_x^2 + y^2/\sigma_y^2)/2 + j\omega x)} \]

(14)

The response of Gabor filter is the convolution of Gabor window with image \( I \), and is given by Eq. (15)

\[ G_{mn}(x, y) = \sum_{s} \sum_{t} H^s(x-s, y-t) \psi^2_{mn}(s, t) \]

(15)
3.2. Gabor local ternary co-occurrence patterns (GLTCOs)

In the proposed method, the Gabor transform with three scales (m) and four directions (0°, 45°, 90° and 135°) are applied on a given image to compute first-order derivatives in eight directions.

Given a center pixel ($g_i$), the GLTCOp is obtained by performing the first-order derivatives on real part of the Gabor transform response as follows:

$$G_{P,R,m,i}(g_i) = \begin{cases} G_{P,R,m,0}(g_i) - G_{P,R,m,0}(g_i); & i = 1 \\ G_{P,R,m,45}(g_i) - G_{P,R,m,45}(g_i); & i = 2 \\ G_{P,R,m,90}(g_i) - G_{P,R,m,90}(g_i); & i = 3 \\ G_{P,R,m,135}(g_i) - G_{P,R,m,135}(g_i); & i = 4 \\ G_{P,R,m,1}(g_i) - G_{P,R,m,0}(g_i); & i = 5 \\ G_{P,R,m,3}(g_i) - G_{P,R,m,45}(g_i); & i = 6 \\ G_{P,R,m,5}(g_i) - G_{P,R,m,90}(g_i); & i = 7 \\ G_{P,R,m,7}(g_i) - G_{P,R,m,135}(g_i); & i = 8 \\
\end{cases}$$

(16)

The GLTCOp is defined as

$$\text{GLTCOp}_m = \begin{bmatrix} f_3(G_{P,R,m,1}(g_i), G_{P,R,m,1}(g_i), \ldots), & ... \\ f_3(G_{P,R,m,2}(g_i), G_{P,R,m,1}(g_i), \ldots), & ... \\ \ldots & \ldots \\ f_3(G_{P,R,m,1}(g_i), G_{P,R,m,1}(g_i), \ldots), & ... \\
\end{bmatrix}$$

(20)

Finally, the histograms are constructed for each scale (m) as similar to the LTCoP.

3.4. Proposed system framework

Fig. 4 illustrates the framework of the proposed system and algorithm for the same is given below.

Algorithm.

Input: Query image; Output: Retrieval results

1. Load the query image.
2. Calculate the first-order derivatives at R and R+1 with respect to the center pixel.
3. Calculate the ternary values.
4. Calculate the co-occurrence between the ternary values.
5. Form the LTCoP which is the ternary pattern.
6. Convert LTCoP into two binary patterns.
7. Construct the histograms.
8. Form the feature vector by concatenating the histograms.
9. Compare the query image with the images in the database using similarity measure.
10. Retrieve the images based on the best matches.

This algorithm is also applied on Gabor transform (GT) sub-bands (with three scales and four directions) for LTCoP with Gabor transform (GLTCOp).

Table 1

MRI data acquisition details [33].

<table>
<thead>
<tr>
<th>Sequence</th>
<th>TR (ms)</th>
<th>TE (ms)</th>
<th>Flip angle (°)</th>
<th>TI (ms)</th>
<th>TD (ms)</th>
<th>Orientation</th>
<th>Thickness, gap (mm)</th>
<th>Resolution (pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MP-RAGE</td>
<td>9.7</td>
<td>4.0</td>
<td>10</td>
<td>20</td>
<td>200</td>
<td>Sagittal</td>
<td>125, 0</td>
<td>176 x 208</td>
</tr>
</tbody>
</table>

Fig. 3 illustrates the comparison between the various features on two sample images which are selected from the different categories of OASIS–MRI database. By visualization we can identify that the sample images are not similar. The histograms of both images (two sample images) using LBP and LDP methods are almost similar. But the histograms of both images using LTCoP are not similar which can be seen in Fig. 3. From Fig. 3 (c), it is clear that the proposed method (LTCoP) is able to differentiate the two sample images as compared to LBP and LDP.
Fig. 5. Sample images from OASIS-MRI database (one image per category).

Fig. 6. (a)–(c) Comparison of the proposed method with other existing methods as function of number of top matches. (d)–(f) Groupwise performance of various methods in terms of ARP on OASIS-MRI database.

Table 2
Performance of LTCoP with different thresholds for ternary value calculation on OASIS-MRI database.

<table>
<thead>
<tr>
<th>Method</th>
<th>Threshold (th)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTCoP</td>
<td>48.50 46.60 46.93 47.88 47.52 47.86 47.07 46.74 46.55 46.41</td>
</tr>
<tr>
<td>LTCoPu2</td>
<td>47.57 46.08 45.72 47.55 47.71 47.55 46.98 46.43 44.44 44.25</td>
</tr>
<tr>
<td>LTCoPriu2</td>
<td>45.46 45.43 46.93 47.57 47.00 46.76 46.05 46.03 45.39 44.20</td>
</tr>
</tbody>
</table>

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3.5. Similarity measure

Feature vector of query image $Q$ is represented as $f_Q = \{f_{Q_1}, f_{Q_2}, \ldots, f_{Q_n}\}$ obtained after the feature extraction. Similarly each image in the database is represented with feature vector $f_{DB_i} = \{f_{DB_1}, f_{DB_2}, \ldots, f_{DB_n}\}; j = 1, 2, \ldots, |DB|$. The goal is to select $n$ best images that resemble the query image. This involves selection of $n$ top matched images by measuring the distance between query image and image in the database $|DB|$. In this paper, four types of similarity distance metrics are used and these are shown below:

$L_1$ or Manhattan distance measure:

$$D(Q, DB) = \sum_{i=1}^{L_1} |f_{DB_i} - f_{Q_i}|$$  

Euclidean distance measure:

$$D(Q, DB) = \left( \sum_{i=1}^{L_2} (f_{DB_i} - f_{Q_i})^2 \right)^{1/2}$$  

Canberra distance measure:

$$D(Q, DB) = \sum_{i=1}^{L_3} \frac{|f_{DB_i} - f_{Q_i}|}{|f_{DB_i}| + |f_{Q_i}|}$$  

d_1 distance measure:

$$D(Q, DB) = \sum_{i=1}^{L_4} \left| \frac{f_{DB_i} - f_{Q_i}}{1 + f_{DB_i} + f_{Q_i}} \right|$$  

where $f_{DB_i}$ is the $i$th feature of $j$th image in the database $|DB|$.

3.6. Evaluation measures

The average retrieval precision (ARP) and average retrieval rate (ARR) judge the performance of the proposed method and those are calculated by Eqs. (25)-(28). For the query image $I_q$, the precision $(P)$ and recall $(R)$ are defined as follows:

$$\text{Precision} : P(I_q) = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}$$  

Recall : $R(I_q) = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the database}}$  

$$\text{ARR} = \frac{1}{|DB|} \sum_{n=|DB|}^{n=10} R(I_q)$$  

3.7. Abbreviations

Given below are the abbreviations used in the analysis of result:

GT: Gabor transform  
LBP: Local binary patterns  
GLBP: LBP with GT  
DBWP: Directional binary wavelet patterns  
LTP: Local ternary patterns  
GLTP: LTP with Gabor transform  
LDP: Local derivative patterns  
GLDP: LDP with GT  
LTrP: Local tetra patterns  
GLTrP: LTrP with Gabor transform  
LTCoP: Local ternary co-occurrence patterns  
GLTCoP: LTCoP with GT  
LTCoPu2: LTCoP with uniform patterns (same is applicable for other patterns)  
LTCoPrui2: LTCoP with rotational invariant uniform patterns (same is applicable for other patterns)

4. Experimental results and discussions

In order to analyze the performance of our algorithm for biomedical image retrieval three experiments were conducted on three different medical databases. Results obtained are discussed in the following subsections.

In all experiments, each image in the database is used as the query image. For each query, the system collects $n$ database
Fig. 7. Query results of the proposed method on OASIS-MRI database.

Fig. 8. Sample images from NEMA-CT database (one image per category).
Fig. 9. Comparison of the proposed method with other existing methods as function of number of top matches on NEMA-CT database.

Table 6
Performance of LTCoP with different thresholds for ternary value calculation on NEMA-CT database.

<table>
<thead>
<tr>
<th>Method</th>
<th>Threshold (th)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTCoP</td>
<td></td>
<td>92.79</td>
<td>92.62</td>
<td>92.59</td>
<td>92.65</td>
<td>92.71</td>
<td>92.79</td>
<td>92.99</td>
<td>93.09</td>
<td>93.31</td>
<td>93.70</td>
</tr>
<tr>
<td>LTCoPu2</td>
<td></td>
<td>91.95</td>
<td>92.40</td>
<td>92.67</td>
<td>92.79</td>
<td>92.96</td>
<td>93.02</td>
<td>92.96</td>
<td>92.76</td>
<td>92.79</td>
<td>92.92</td>
</tr>
<tr>
<td>LTCoPriu2</td>
<td></td>
<td>90.66</td>
<td>91.54</td>
<td>91.90</td>
<td>91.62</td>
<td>91.90</td>
<td>91.79</td>
<td>91.35</td>
<td>91.11</td>
<td>91.10</td>
<td>90.80</td>
</tr>
</tbody>
</table>

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images \(X = (x_1, x_2, \ldots, x_n)\) with the shortest image matching distance is given by Eq. (24). If \(x_i; i = 1, 2, \ldots, n\) belong to the same category of the query image, we say the system has correctly matched the desired.

4.1. Experiment #1

The Open Access Series of Imaging Studies (OASIS) [33] is a series of magnetic resonance imaging (MRI) dataset that is publicly available for study and analysis. This dataset consists of a cross-sectional collection of 421 subjects aged between 18 and 96 years. The MRI acquisition details are given in Table 1.

For image retrieval purpose we grouped these 421 images into four categories (124, 102, 89, and 106 images) based on the shape of ventricular in the images. Fig. 5 depicts the sample images of OASIS database (one image from each category).

From experiment #1, the following inference is drawn for the performance of proposed method with other methods in terms of average retrieval precision (ARP).

1. LTCoP outperforms the LDP, LTP, LTP, LBP (without uniform two, with uniform two and rotational invariant uniform two) and DBWPu2 in terms of ARP.

2. GLTCoP outperforms the GLDP, GLTP, GLTPr, GLBP (without uniform two, with uniform two and rotational invariant uniform two) and DBWPu2 in terms of ARP.

Fig. 6(a)–(c) shows the retrieval performance of the proposed method and other existing methods in terms of ARP. Fig. 6(d)–(f) illustrates the group wise performance of various methods with and without the Gabor transform in terms of ARP. From Fig. 6 and above observations, it is evident that the proposed method outperforms the other existing methods. Tables 2 and 3 summarize the performance of the proposed method (LTCoP/GLTCoP) with different thresholds for ternary value calculation on OASIS–MRI database. From Tables 2 and 3, it is observed that the thresholds ‘0.1’ and ‘0.1’ are showing better performance for LTCoP and GLTCoP respectively. Table 4 illustrates the performance of the proposed method with various similarity measures in terms of ARP on OASIS–MRI database. From Table 4, it is clear that the \(d_1\) similarity measure shows better performance for LTCoP and GLTCoP. Table 5 illustrates the performance of the proposed method with various similarity measures in terms of ARP on NEMA–CT database. From Table 5, it is evident that the \(d_1\) similarity measure shows better performance as compared to other similarity measures.

4.3. Experiment #3

Vision and image analysis (VIA) group and international early lung cancer action program (1-ELCAP) created a computer tomography (CT) dataset [35] for the performance evaluation of different computer aided detection systems. These images are in DICOM (digital imaging and communications in medicine) format. The CT scans were obtained in a single breath hold with a 1.25 mm slice thickness. The locations of nodules detected by the radiologist are also provided. The CT scan data acquisition details are given in Table 9. For experiments we have selected 10 scans. Each scan has 100 images with resolution 512 × 512. Further, ROIs were

### Table 8

<table>
<thead>
<tr>
<th>Method</th>
<th>Distance measure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(L_1)</td>
</tr>
<tr>
<td>LTCoP</td>
<td>92.24</td>
</tr>
<tr>
<td>LTCoPu2</td>
<td>91.82</td>
</tr>
<tr>
<td>LTCoP(d_1)</td>
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</tr>
<tr>
<td>GLTCoP</td>
<td>94.87</td>
</tr>
<tr>
<td>GLTCoPu2</td>
<td>94.12</td>
</tr>
<tr>
<td>GLTCoP(d_1)</td>
<td>93.65</td>
</tr>
</tbody>
</table>

### Table 9

<table>
<thead>
<tr>
<th>Data No. of slices</th>
<th>Resolution</th>
<th>In-plane resolution</th>
<th>Slice thickness (mm)</th>
<th>Tube voltage (KV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>W1-10</td>
<td>512 × 512</td>
<td>0.76 × 0.76</td>
<td>1.25</td>
<td>120</td>
</tr>
</tbody>
</table>

### Table 7

<table>
<thead>
<tr>
<th>Method</th>
<th>Threshold ((t))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.1</td>
</tr>
<tr>
<td>LTCoP</td>
<td>94.49</td>
</tr>
<tr>
<td>LTCoPu2</td>
<td>94.81</td>
</tr>
<tr>
<td>GLTCoPu2</td>
<td>94.34</td>
</tr>
</tbody>
</table>

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Fig. 11 depicts the sample images of VIA/I-ELCAP database (one image from each category).

Fig. 12 shows the retrieval performance of the proposed method and other existing methods in terms of ARP and ARR. From Fig. 12, it is evident that the proposed method outperforms the other existing methods. Tables 10 and 11 summarize the performance of the proposed method (LTCoP/GLTCoP) with different thresholds for ternary value calculation on VIA/I-ELCAP–CT database. From Tables 10 and 11, it is observed that the thresholds $'2'$ and $'0.1'$ are showing better performance for LTCoP and GLTCoP respectively. Table 12 illustrates the performance of the proposed method with various similarity measures in terms of ARP on VIA/I-ELCAP–CT database. From Table 12, it is clear that the $d_1$ similarity measure shows better performance as compared to other similarity measures.

### 4.4. Feature vector length V/S performance

Table 13 shows the feature vector length for a given query image using LBP, GLBP, LDP, GLDP, LTP, GLTP, DBWP, LTCoP and GLTCoP. From Table 13, it is clear that the feature vector length of GLTCoP is 13.3 and 2 times less as compared to DBWP and GLDP respectively and is outperforming the DBWP and other existing methods in terms of ARP and ARR on three different biomedical databases.

### 5. Conclusions

In this paper, a new image indexing and retrieval algorithm is proposed using local ternary co-occurrence patterns (LTCoP). The LTCoP encodes the occurrence of similar ternary edges in an
image. The performance of the proposed method is also analyzed with different thresholds for ternary value calculation. The performance improvement of the proposed method has been compared with the LBP, the LTP and the LDP on three benchmark biomedical image databases. The result after being investigated shows a significant improvement in terms of precision, recall, ARR and ARP as compared to LBP, LTP and LDP on respective databases.

Due to the effectiveness of the proposed method, it can be also suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc.
We would like to thank the editor and anonymous reviewers for insightful comments and helpful suggestions to improve the quality of the paper.

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